On User Choice for Android Unlock Patterns

Marte Loge,
NTNU, Norway

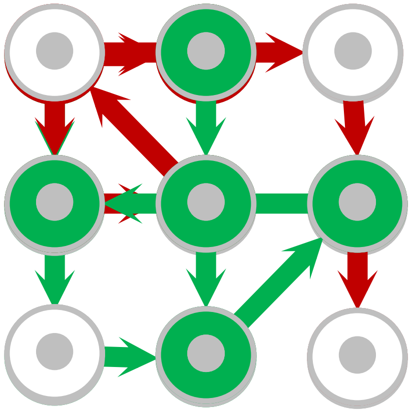
Markus Dürmuth
RUB, Bochum

Lillian Rostad
NTNU Norway

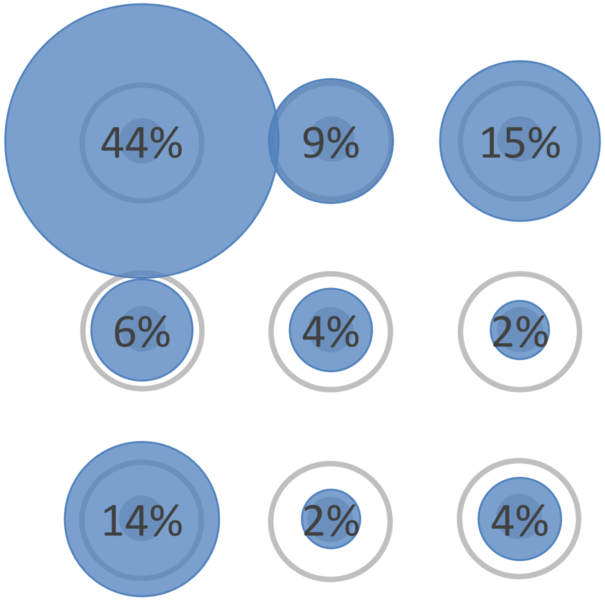
EuroUSEC 2016, Darmstadt

Graphical passwords
Android unlock patterns

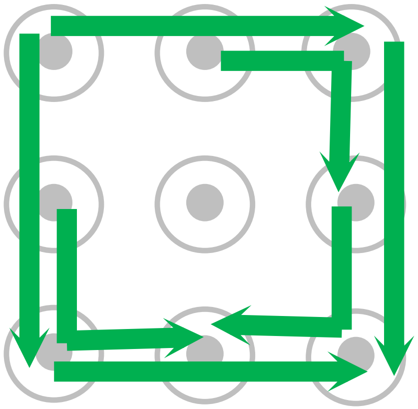
- Graphical information is easier to remember and easier to enter on touchscreens
- Android uses a restricted Pass-Go scheme
- Probably one of the most studied graphical authentication schemes



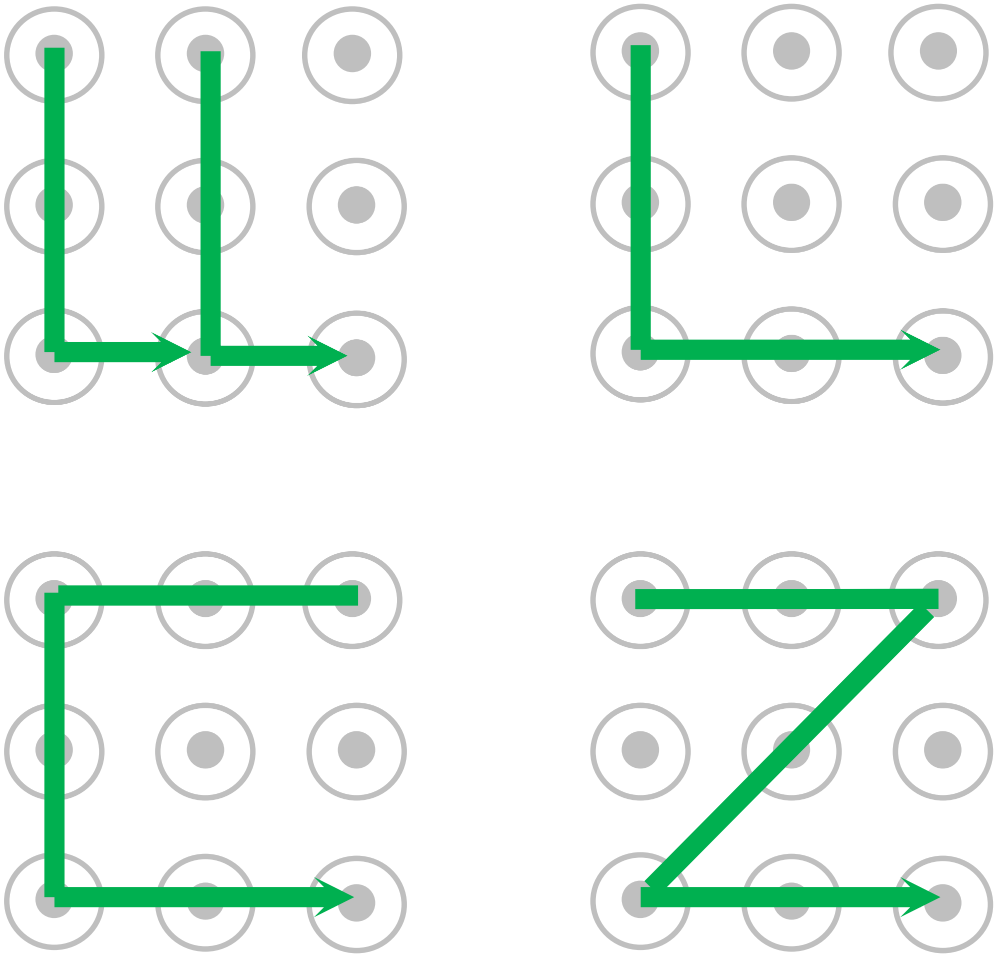
Frequent starting points



Frequent 3-grams

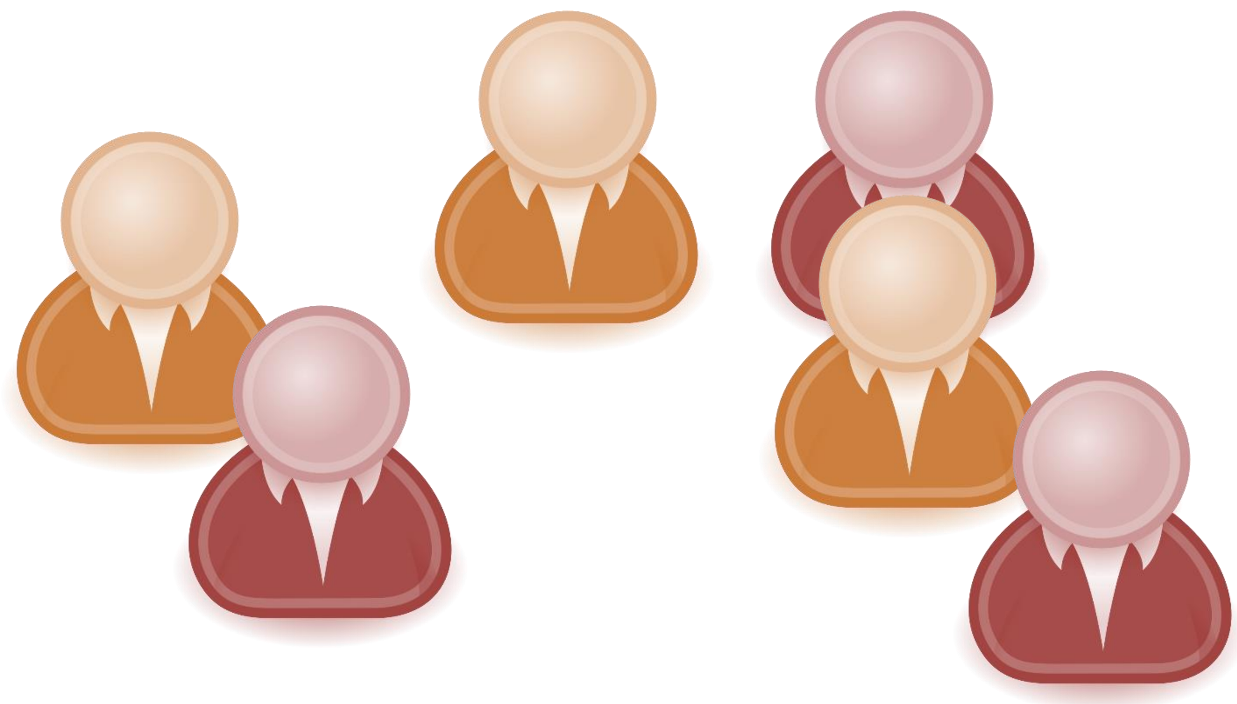


Frequent “letters”

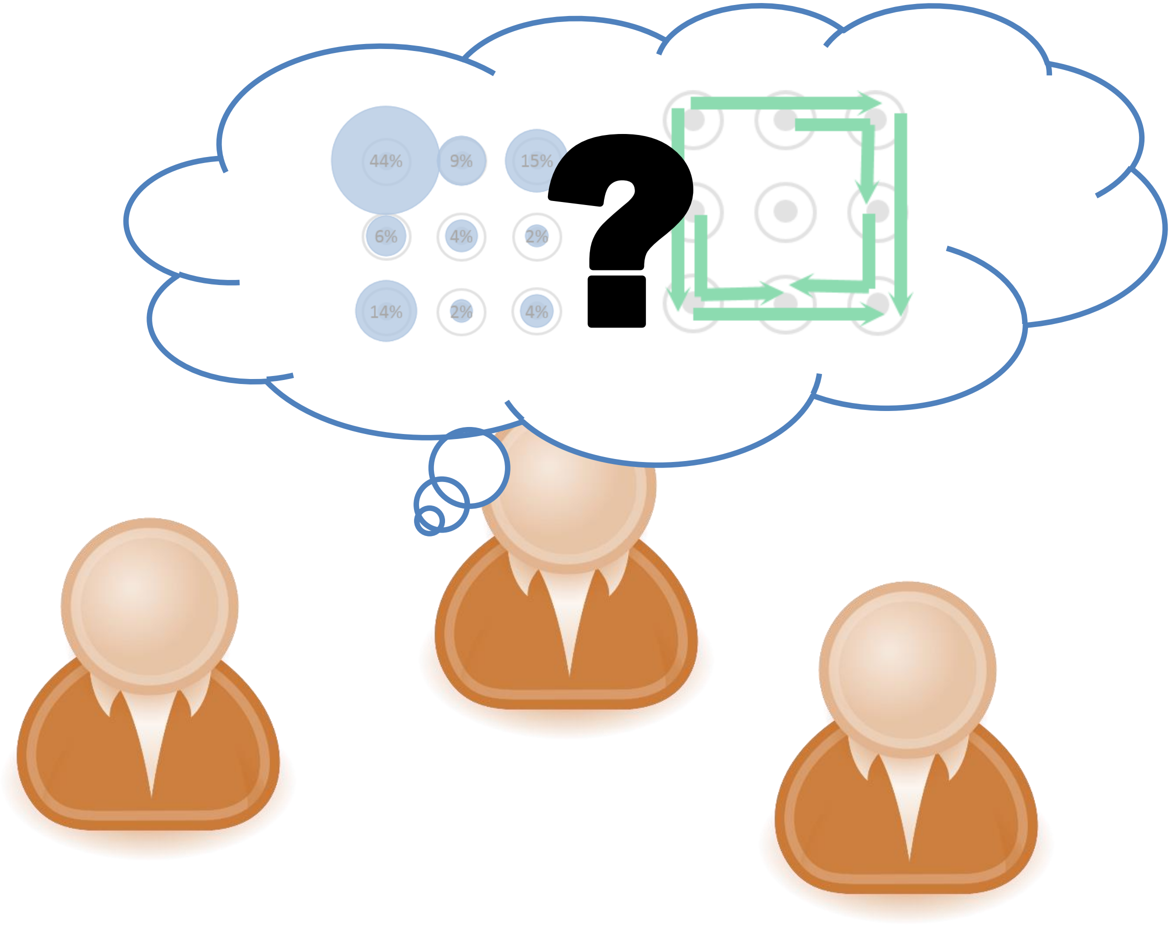



44%
9%
15%
6%
4%
2%
14%
2%
4%

User is female



User is female, with experience in IT security…



Why should we care?

- More precisely estimate adversaries capabilities
- Better strength meters
- Tailor security measures to specific users

Data collection

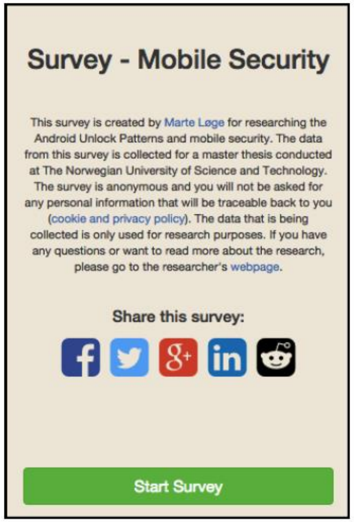
User study

- Online study on participants own devices
- Snowball sampling via mailing lists, social networks, word of mouth

- 800 participants
- Predominantly
  - below 30
  - from Norway
  - male
  - with experience in IT security

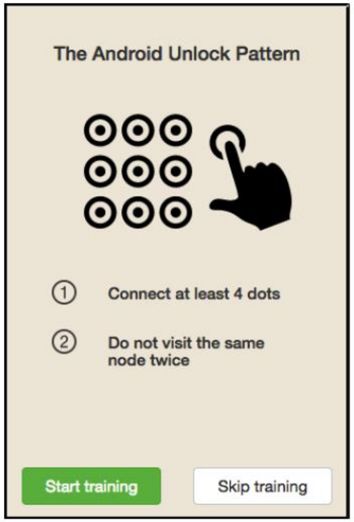
		Total	In %
Gender	male	529	66%
	female	278	34%
Handedness	right	690	88%
	left	97	12%
IT or IT security	expert	470	59%
	non-expert	332	41%
Writing-orientation	left-to-right	792	98%
	right-to-left	8	1%
	top-to-bottom	7	1%
Age	16-19	22	3%
	20-24	331	41%
	25-29	169	21%
	30-34	96	12%
	35-39	82	10%
	40-49	73	9%
	50+	30	4%
Hand-size	small	103	13%
	medium	406	50%
	large	255	31%
	extra-large	49	6%
Country	Norway	517	64%
	USA	115	14%
	Germany	33	4%
	Czech Republic	31	4%
	UK	22	3%
	Russia	13	2%
	Rest (<10 each)	75	9%
Total $^{(*)}$		802	100%

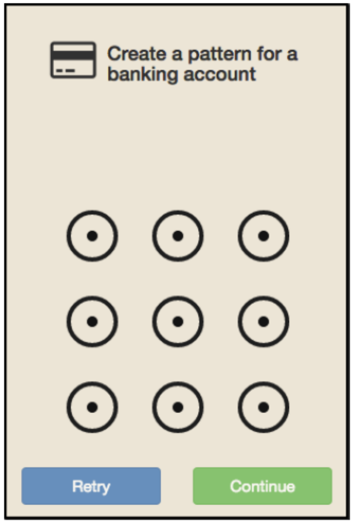
TABLE I. STATISTICS OF THE PARTICIPANTS. $^{(*)}$ NOTE THAT 802 PARTICIPANTS COMPLETED THE ENTIRE STUDY, BUT A FEW PARTICIPANTS ANSWERED SOME QUESTIONS BEFORE LEAVING. THUS SOME QUESTIONS HAVE MORE THAN 802 ANSWERS.)



1) Intro and consent

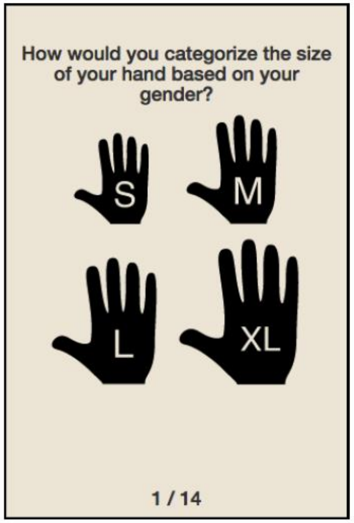
2) Explanation and (opt.) tutorial





3) Collect data

4) Explanation and tutorial



Results

Measuring strength of patterns

- We use Uellenbeck et al.'s Markov models for strength estimation.
- For an *n*-gram model:

$$\hat{p} = P(c_1, \dots, c_m) \approx P(c_1, \dots, c_{n-1}) \prod_{i=n}^{m} P(c_i | c_{i-n+1}, \dots, c_{i-1})$$

- We use $-\log(\hat{p})$ as strength
- We use 3-grams, Laplacian smoothing, and train on data collected by Uellenbeck et al.

Results for the entire dataset
Pattern creation times

All differences significant*

=> The (fictive) scenario has an influence on the users

	Creation times
Shopping	7.06 sec
Smartphone	6.45 sec
Bank	8.08 sec

* Mann W-U, 95% confidence, Bonferonni-correction

Results for the entire dataset
Pattern strength

- Patterns in the Bank scenario significantly stronger than in shopping and smartphone scenarios
- No sign. difference between shopping and smartphone

	Shopping	Smart-phone	Bank
Avg. Size	5.54	5.40	5.92
Avg. length	5.05	4.92	5.67
1st Qu.	5.84	5.85	6.72
median	7.98	8.16	9.35
3rd Qu.	11.12	11.17	13.11

The influence of personal traits

RUB

Gender

- Gender has an influence for two scenarios

Gender	Female	Male	P
Shopping	7.66	8.15	0.1082
Smartphone	7.57	8.47	0.0204 (**)
Bank	8.50	9.79	0.0042 (**)

Handedness

- No significant differences

Handedness	left	right	P
Shopping	7.66	8.10	0.89
Smartphone	7.84	8.29	1
Bank	8.90	9.53	0.257

The influence of personal traits

Experience in IT or IT security

- No sign. influence of experience in IT security

IT experience	yes	no	P
Shopping	8.15	7.66	0.15
Smartphone	8.29	7.86	0.07 (*)
Bank	9.43	9.09	0.32

But:

- sign. influence on the *pattern length* in the Banking scenario ($p < 0.0001$)

The influence of personal traits
Correlations

RUB

Age

- Significant influence in the bank scenario

Age	ρ	P
Shopping	-0.08	0.16
Smartphone	-0.04	1
Bank	-0.11	0.0099 (**)

Handsize

- No significant influence

Handsize	ρ	P
Shopping	0.018	1
Smartphone	0.041	1
Bank	0.0264	1

Limitations

RUB

- Snowball sampling and bias in the participants
- How to measure pattern strength?
- Writing direction interesting, but not sufficient data

Why should we care?

- More precisely estimate adversaries capabilities
- Better strength meters
- Tailor security measures to specific users

Related work

- Related work by Aviv et al. considers influence of personal traits on specific characteristics
  - gender, handedness, locale

- PassFaces
  - Influenced by gender and race

- Text passwords
  - Influenced by language, …

Thank you